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Large scale simulation of CO_2 emissions caused by urban car traffic: An agent-based network approach

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ABSTRACT

CO_2 emissions caused by private motorized traffic for the city of Graz, a typical European inland city with about 320 000 citizens, are investigated. The main methodology is a newly developed agent-based model that incorporates empirical data about the mobility behavior of the citizens in order to calculate the traveled routes, the resulting traffic and subsequent emissions. To assess the impact of different policies on CO_2 emissions, different scenarios are simulated and their results are compared to a base line scenario. The model features a local and temporal resolution, effects like congestion and stop-and-go traffic as well as commuters to and from other regions. In addition to the evaluation of certain policies (like a focus on electric cars, telecommuting or an improvement of the road infrastructure), a method is provided, that makes it possible to compare many diverse scenarios, featuring technological changes, societal changes or changes in the road network, all within the same framework. The findings suggest that one of the most promising strategies to decrease urban CO_2 emissions is to focus on the use of electric cars, especially if it is combined with offering alternatives to private car traffic and incentives for telecommuting. Banning the use of old cars only yields a significant result if a large amount of cars is affected, which would make such a policy difficult to implement. Expanding the road network has no significant positive effect and may even encourage using cars, therefore leading to even more CO_2 emissions. Due to its flexible structure the presented model can be used to evaluate policies beyond what is presented in this study. It can easily be adapted to other conditions and geographical regions.

1. Introduction

The role of cities in the mitigation of climate change and the adaption to its effects is of high importance for various reasons. First of all, more than 50% of the world population lives in cities (UN DESA, 2014). Additionally, cities are responsible for more than 75% of the global energy consumption (Gouldson et al., 2016) and the global greenhouse gas (GHG) emissions (Change, 2015). However, cities do not only cause the majority of the GHG emissions (Mi et al., 2015), they are also highly affected by their consequences like climate change (Geng et al., 2014). On the other hand, cities are also in the unique position to tackle the challenges of climate change. They have the means to find and implement various policies that could help in the mitigation of climate change (Rosenzweig et al., 2010). The International Energy Agency (IEA) estimates that urban energy use is responsible for about 76% of all global emissions (IEA, 2009). A significant portion of urban energy use is caused by traffic. Especially here, the public sector has ample opportunities to influence the behavior of the citizens with various policies. A good public transport system, certain incentives for the use of electric cars, or the strict regulation of cars that emit too much CO_2, can have a huge impact on the GHG emissions of the city.

The problem with such policies is that it is difficult to assess their impact, since one would need a complex, yet large-scale model to predict all effects that a change in the traffic system or a change in mobility behavior could have. There are various approaches to tackle this challenge (see section 2 for details on them), but currently there is no method that is fast enough to evaluate a satisfyingly large number of variations of parameters of a policy scenario, while being flexible enough to consider technological, social, and juridical changes within the same framework. In order to fill this research gap, this study introduces a novel way of traffic simulation that is agent-based, yet all of the interaction between the agents is considered on the base of a network approach, which

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drastically speeds up simulation time. The presented method is then applied to the city of Graz, an Austrian City with a population of about 320 000 people, serving as a typical example of a city of this size, with a simple structure (no multiple city centers, no huge industrial clusters, consistent population density within each district).

This manuscript is organized as follows: Section 2 gives a short introduction to state-of-the-art approaches to traffic modeling, listing advantages and disadvantages and detailing differences to the presented method. Section 3 gives further details of the model. Results of various scenarios are presented in section 4. Section 5 concludes with policy recommendations as well as this study's contribution to the advancement of the state-of-the-art.

2. Methodology

There are many different ways to simulate traffic and all approaches have unique advantages and disadvantages. Many traffic simulations are constructed bottom-up, i.e. they start from the behavior of single vehicles and aggregate to obtain macro-scale results. Maybe the most famous model, based on Cellular Automata, is the Nagel-Schreckenberg model (Nagel and Schreckenberg, 1992). It starts out from very simple rules and is able to predict complex phenomena like the emergence of traffic jams. Beyond that, there are more complex, agent-based models that can also include pedestrian movement in the form of the Social Force Model (Helbing and Molnar, 1995), and a more complicated car following model (Wiedemann and Reiter, 1992). Most prominent are the commercially available PTV VISSIM (Vissim, 2008) and the open-source projects MatSIM (Balmer et al., 2009) or SUMO (Krajzewicz et al., 2002). For a more detailed review on traffic simulations, see (Kotusevski and Hawick, 2009). Traffic models are of course primarily developed to predict and analyze traffic flow, but they can be augmented by emission models, like for example the Comprehensive Modal Emission Model (Barth et al., 2000), to gain accurate predictions on traffic emissions (Wang and Fu, 2010). The main methods to simulate traffic-caused emissions are bottom-up approaches (mostly agent-based and on the micro-scale) that can also produce good results in an urban environment (Hülsmann et al., 2011). However, these models have their focus on accurately depicting the travel time of each vehicle, which is computationally very expensive and not necessarily required for investigating CO_2 emissions.

On the other end of the spectrum, and especially relevant for emission estimation, there are top-down models. For example a statistical emission model, that requires very little input, but is sufficiently complicated to produce reasonable results was developed (Cappiello et al., 2002). In general, top-down models can have many advantages, for example they do not rely on detailed origin-destination surveys and are numerically relatively cheap (Tuia et al., 2007). However, they lack the microscopic detail that bottom-up approaches offer. Top-down approaches are computationally cheaper, but often lack the flexibility that is needed to run diverse scenarios, since they heavily rely on statistical data that cannot be adapted easily for all interesting scenarios. Hybrid approaches, i.e. simulations that depict all road traffic in a way abstract enough to allow for fast computation, are also very promising for investigating emissions (Cetin et al., 2003).

A different approach is using a dispersion model to calculate emissions (Berkowicz et al., 2006). Dispersion models use some form of emission estimation, like the COPERT software (Ntziachristos et al., 2000) to find out what amount of emissions are generated by roads and then add a dispersion model, like the Operational Street Pollution Model (Berkowicz, 2000) in order to gain local resolution of the dispersion of these emissions. However, it should be noted that the local resolution of emissions is not very relevant, when investigating CO_2 emissions.

Even though there are currently many approaches that are suitable to simulate urban traffic emissions (see Table 1 for an overview), Grote et al. find that there is still a high demand for new ways of modeling urban traffic emissions, since currently Local Government Authorities do not necessarily have the right options to meet their requirements (Grote et al., 2016). Additionally, each state-of-the-art method has certain disadvantages that make it difficult to evaluate all policies and scenarios of interest within the same framework. Therefore, a novel model is needed to fulfill the following requirements:

- to be fast enough to be computed for many different scenarios often enough to make reliable predictions,
- to include accurate information about used cars and their emissions,
- to depict increased emissions due to congestion and stop-and-go traffic without the need for statistical data about road congestion,
- to require no exact origin-destination data, yet to produce realistic path origins and destinations,
- to include the road infrastructure, and
- to consider additional trip information, like for example the purpose of a trip (e.g. working trip, shopping trip, etc.)

The main advantages of the proposed model, compared to current state-of-the-art traffic emission models, are the following:

- its 1:1 scale, i.e. each citizen is represented in the model,
- its fast computation time (a 24-h scenario can be calculated in roughly 3 h using a single processor core, i.e. significantly faster than real-time)
- that it does not depend on origin-destination data, but is based on input parameters that are easy to modify to correspond to various scenarios
- that it is flexible enough to evaluate various scenarios regarding juridical, social, or technological changes
- that it can adapt to various possible future developments, like population growth or urban sprawl

A comparison between a traditional and the presented approach is given in Fig. 1. Note the difference in input data, which makes the model better suited to support decision-makers. Additionally, it is fast and flexible enough to evaluate many different scenarios within the same framework. It is possible to investigate social changes (e.g. changing the mobility behavior of the agents), technical changes (e.g. changing the emission rates of cars), juridical changes (e.g. banning old cars within the city) or changes in the road infrastructure, and therefore compare fundamentally different policies and their impact on CO_2 emissions within the same model.

3. The model

The purpose of this model is to calculate the emissions caused by urban car traffic. This is achieved in several steps. First the road network is generated, as detailed in section 3.1. Then the simulated agents use this network to make realistic trips. For this, origin-destination data is required, which is generated as detailed in section 3.2. In order to obtain realistic road usage, commuters with residences outside the city limits were included as well, using entry points generated from statistical information (Statistik Austria, 2011). Note, that the actual update order of the agents is of no relevance, since all interactions between agents are included later on, when all the trips have been determined. With precise

Table 1
Overview of the most prominent approaches for investigating emissions caused by motorized traffic, together with their main advantages and disadvantages.

Approach	Type	Advantages	Disadvantages
Microscopic traffic simulation relying on origin-destination data combined with an emission model	Bottom-Up	- Paths are exact - Precise emission estimation	- Long computation time - Origin-destination data is rare
Microscopic traffic simulation independent of origin-destination data combined with an emission model	Bottom-Up	- Does not need origin-destination data - Precise emission estimation	- Long computation time - Origin-destination information needs to be generated somehow
Statistical model	Top-Down	- Short computation time - Simple way to include additional information on driving behavior etc.	- Difficult to run scenarios for which no statistical data is available
Dispersion model	Top-Down	- Short computation time - Local resolution	- Difficult to include specifics of driving behavior or type of vehicles used

knowledge about how many cars use each road during each hour it is possible to estimate if traffic is flowing freely, or if stop-and-go traffic occurs, as explained in section 3.3. The amount of emitted CO_2 is then calculated from traffic flow, the traveled distance and the type, size and age of the car used, according to the formulas presented in section 3.4. The scenarios presented in section 3.5 give an overview of the capabilities of the model, but of course many other scenarios would be possible.

3.1. Generating a network representation of the road network

For a realistic representation of the city, including all the roads and relevant data (speed limits, districts, width of each road, one-ways …), a network representation of the road system is generated, in which the nodes represent intersections and the edges represent the streets connecting them. The necessary geographical data was exported from OpenStreetMap (OSM) (OpenStreetMap contributors, 2017) in April 2017. The software library OSMnx (Boeing, 2017) was used to download information on the urban area of Graz and convert it into a simplified road network of all drivable public streets. This network structure already includes most of the necessary information (geographic coordinates, length of roads, number of lanes, maximum allowed speed, …). Additional information is added either through simple calculation (travel time) or through an additional OSM export (suburb). Since this process can be done for any region, it should be possible to apply the presented model to other cities or expand it to larger areas. The resulting street network used in the simulation is visualized in Fig. 2.

3.2. Generating realistic trip data

One of the main challenges of every transport simulation is obtaining origin-destination data. For small scale models it is possible to get this data directly from surveys, in order to accurately describe each trip within the scope of the model. However, for larger scales, one needs to rely on some form of approximation, since it is impossible to get exact origin-destination data for every single citizen in a large urban area. One possibility is to generate the origin-destination data from land-use plans and assume that most routes connect residential zones with commercial or industry zones. However, this approach is somewhat abstract and it is

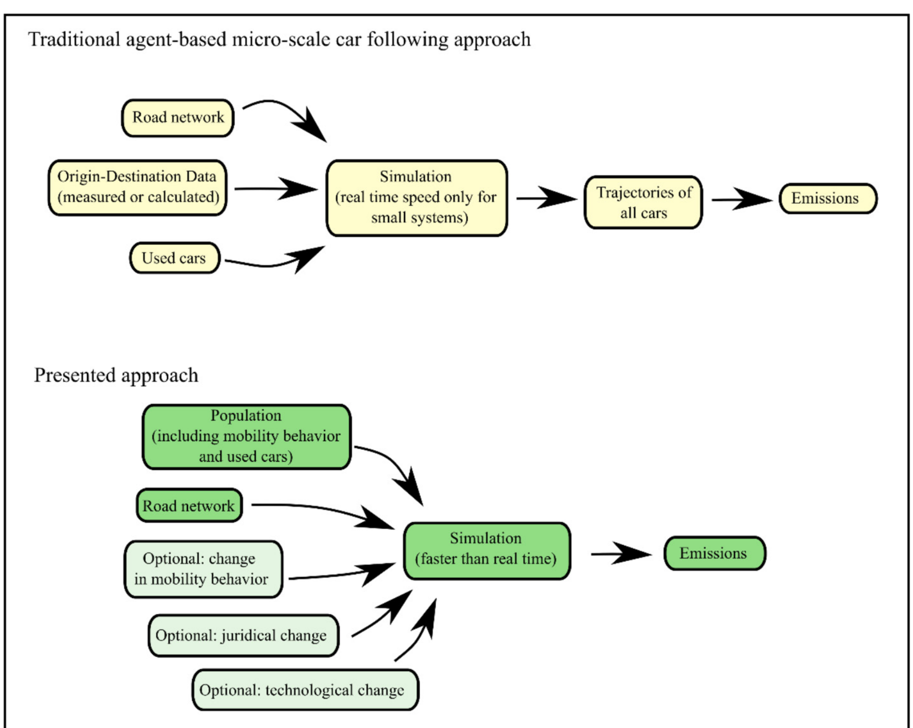

Fig. 1. The input parameters used in the presented model are better suited for evaluating scenarios and calculating emissions is faster.

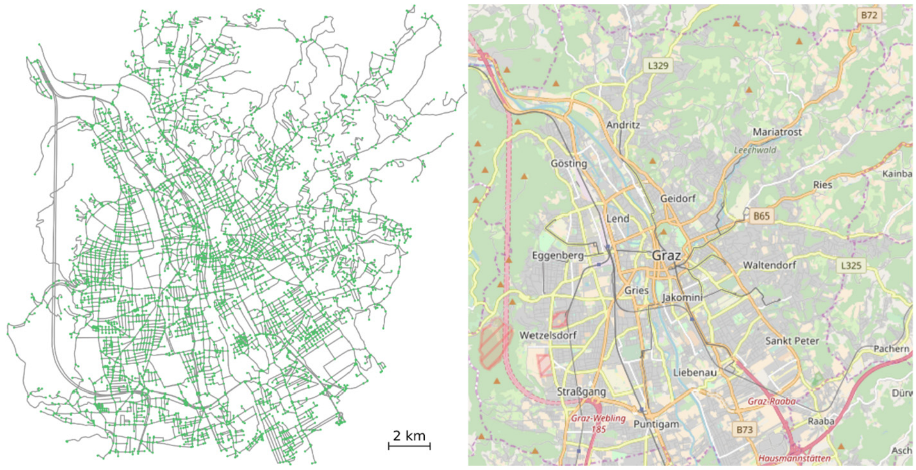

Fig. 2. The network representation of the investigated road system (left) in comparison to a street map of the same area (right). The relevant road points (green nodes) are connected by roads (gray edges). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

difficult to include specifics of mobility behavior.

In the agent-based approach presented in this paper, the generation of origin-destination data is novel in the way that it combines empirical survey data with an agent-based method on a large scale. The empirical foundation is a survey performed by the Austrian Ministry for Transport, Innovation and Technology (Tomschy et al., 2016). In this survey, more than 18 000 respondents from Austria described their mobility routines (distances, purposes, means of transport, …) in a detailed and standardized way. Included in this survey is also sociodemographic information, details about owned cars and specifics of each trip. This origin-destination data is therefore very rich, most importantly because the kind of used cars (overly relevant for emissions) and the purpose of each trip are known.

It is intuitive to restrict the amount of data to respondents that live in a city that is comparable to the analyzed city in terms of size. In this study such a truncation is performed, by using only data from residents of Graz, which provided a set of 883 responders. Each responder reported their mobility behavior on two separate days, distributed around the whole year, so that a representative sample of 1766 days of mobility could be obtained. The crucial step was to generate precise origin-destination data from this survey data for all trips of all agents. The origin-destination data should of course be based on the real trips, done by the responders, but must not match them one-to-one, since then only routes used by the responders would be within the scope of the model. Another challenge was the scale of the model: since the model should be 1:1, trip data for all citizens is necessary. Therefore, a pool of possible mobility behaviors was generated, including all relevant data, like amount of trips, time of the trips, length, purpose and used mode of transportation, but not including exact origin and destination points.

Origin points of each agent are chosen, utilizing information about population density and age distribution in each district, extracted from the population register data of the city of Graz (Stadt Graz, 2017a). Then a number of trips, appropriate for the agent in question, is selected from the pool of trips. The relevant data of one such trip is the purpose of the trip, the used method of transport, the time, and the total distance traveled. The destination point is then selected as a random point, with a distance matching the trip distance up to a small acceptance interval. In that regard, paths and therefore distances between points are not calculated as shortest paths, but as fastest paths. This leads to a more realistic agent behavior. The destination point then becomes the origin point for the next trip and the process is repeated until all agents complete all their trips for the day.

3.3. Agent-based integration of congestion and traffic jams

One of the main motivations of an agent-based approach is the possibility to include micro-scale effects like traffic jams and congestion in large-scale simulations. Especially in an urban area, congestion cannot be neglected. While some roads are used rarely, others suffer from heavy congestion or even stop-and-go traffic during periods of peak activity. This leads to big variations in emissions, since CO_2 emissions roughly double in stop-and-go traffic (Infras, 2010). It is therefore paramount to include information about congestion and traffic jams when simulating car emissions in an urban area.

Unfortunately, statistical data focuses on traveled distance and travel time, but reliable data about the fraction of time spent in stop-and-go traffic is rare and of course very sensitive to the specifics of the city and the roads in question. However, this data is necessary in order to gain correct results of the status quo and is even more important when investigating certain scenarios that may have significant effects on urban traffic flow. To gain a complete understanding of which roads are congested at which times of the day the following method is used.

In a first step, the model calculates the number of cars driving on each road in the investigated system at any given time (see section 3). To determine if this traffic flow can be handled by the road or if congestion effects would emerge, the calculated number was compared with the capacity of each road. Information about the width of the roads, the number of lanes and whether or not this is a one-way street is already available in the model. This information suffices to obtain a valid estimate for the daily traffic capacity C (FGSV, 2006). Due to an uneven distribution over the day, C cannot be simply divided by 24, but special conversion factors were used to obtain the hourly traffic capacity C_h (Höfler, 2004), leading to

$$C_h = L_{eff} * 750 \ \frac{cars}{hour}$$

where L_{eff} is the effective number of lanes, which is the actual number of lanes (if known) or the following approximate values: 0.8 for roads narrower than 5.5 m, 2 for roads between 5.5 and 7.5 m, and 2.6 for roads wider than 7.5 m (Höfler, 2004). For two-way roads this number is divided by 2, since only half of the

lanes can be used in one direction. The next step is to calculate the load quotient a from the number of cars per hour q_b and the hourly traffic capacity C_h (Höfler, 2004) via

$$a = \frac{q_b}{C_h}$$

The load quotient a yields information about the traffic flow. A load quotient below 0.75 can be interpreted as free flowing traffic, a load quotient between 0.75 and 0.9 means a constrained traffic flow and a load quotient above 0.9 results in stop-and-go traffic (Höfler, 2004). Each of these traffic modes has a certain emission factor with regard to CO_2. While free flowing urban traffic has an emission factor of 1.00, constrained traffic leads to an emission factor of 1.25 (i.e. 25% more CO_2 emissions) and stop-and-go traffic results in an emission factor of 2.00 (Infras, 2010). This emission factor is then multiplied to the emissions that would be caused by free flowing traffic, which are calculated from the type, age and size of the car (see section 3.4).

3.4. Calculating CO_2 emissions

The effective CO_2 emissions of cars depend on many different factors, like car size, used fuel, engine, and other technical properties. The model at hand differentiates between diesel and petrol engines and three different car sizes: compact cars (<1150 kg), mid-size cars (between 1150 kg and 1550 kg) and large cars (>1550 kg). In addition, the year the car was built is taken into consideration, to account for various improvements in engine design over the years.

Standard emissions of these types of cars were obtained from (Pötscher, 2016) and adjusted for inner city traffic, under the assumption that fuel consumption in urban traffic exceeds average fuel consumption by 13.5%, conforming to the standardized difference between “combined fuel consumption” and “inner city fuel consumption”. This leads to the values presented in Table 2.

These values are valid for cars built in 2014 and need to be adjusted for all cars built in a different year. The average change in emission is taken from the statistics of the emissions of newly licensed cars (Pötscher, 2016) and is different for petrol and diesel engines. In addition, there is a change in trend in the year 2007, leading to four different factors, given in Table 3.

The effective CO_2 emissions E can then be calculated from the standard emissions for the correct type of car E_{2014}, the relative change in emission RC_1 and RC_2, and the year the car was built Y. For cars built during or after 2007, the following formula is used:

$$E = E_{2014}*(1 + (2014 - Y)*RC_2)$$

For cars built during or before 2007, the following formula is used:

$$E = E_{2007}*(1 + (2007 - Y)*RC_1)$$

where

$$E_{2007} = E_{2014}* (1 + (2014 - 2007)*RC_2) = E_{2014}*(1 + 7*RC_2)$$

Note, that naturally both formulas yield the same result for cars built in 2007. Results of evaluating these equations are given in Fig. 3.

This formula generates a good approximation to actual emissions: Looking at statistical values for the emissions of an average compact car (in this example a Ford Ka from 2011) one finds 139 g/km. The formula evaluated for a car of this size and age yields a result of 143 g/km, leading to an error of less than 3%.

Table 2
Average emission factors E2014 for different car sizes and different engine types.

CO_2 emissions in g/km (*E2014*)	Compact car (S)	Mid-size car (M)	Large car (L)
Petrol	132	145	204
Diesel	110	127	166

Table 3
Yearly relative change of emissions for diesel and petrol engines before and after 2007.

Relative change in emission/year	Pre 2007 (*RC1*)	Post 2007 (*RC2*)
Petrol	0.0114	0.0267
Diesel	0	0.0244

3.5. The scenarios

With this model of urban traffic, different scenarios were run to investigate various policies and their impact on CO_2 emissions. In a base line scenario, the status quo was simulated, in order to get a benchmark for further comparison. An overview of the scenarios is given in Table 4.

Scenario 1 investigated the impact of an increasing number of electric cars in the city. This scenario is of high relevance since currently there are several initiatives on the way to promote the use of electric cars, like investing in a better charging infrastructure (Dong et al., 2014), purchase subsidies (Helveston et al., 2015; Hirte and Tscharaktschiew, 2013; Holtsmark and Skonhoft, 2014) or other incentives, like free parking (Mueller and de Haan, 2009; Sierzchula et al., 2014). If these policies take effect, the number of electric cars used in the urban area should increase. However, it is very difficult to assess how effective these policies will be. Therefore, in order to evaluate the effects on CO_2 emissions, the model was used to simulate a range of possible replacement scenarios. Electric car rates ranging from 1% (meaning 1% of all diesel or petrol engines will be replaced by electric engines) to 20% are considered. In the model, this scenario was implemented by changing the cars in use according to the rate of electric cars. Diesel and petrol fueled cars were selected randomly for replacement. Since only CO_2 emissions resulting directly from the use of the car are within the scope of the model, and not those from the production or transportation of the fuel or electric energy, a CO_2 emission of 0 g/km for

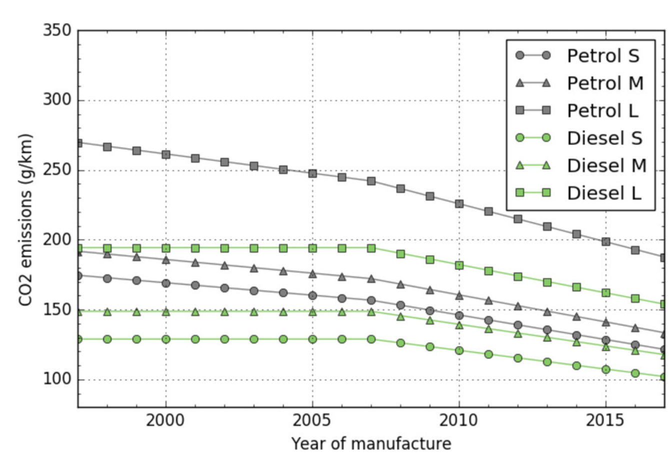

Fig. 3. Average emissions for compact cars (S, circle), mid-size car (M, triangle) and large cars (L, square) with diesel engine (green) and petrol engine (grey) depending on the year they were manufactured in. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Overview of scenarios.

Scenario nr.	Scenario name	Scenario description
1	Electric cars	Increase number of electric cars
2	Remove old cars	Ban old cars
3	Telecommuting	Reduction of work trips due to telecommuting
4	Alternatives to cars	Using car alternatives for short distances
5	Expanding roads	Increase nr. of lanes for most congested road sections
6	Combination	Combination of scenario 1, 3 and 4

electric cars is assumed. With electric energy being provided by CO_2 neutral sources, this would also be valid if CO_2 generated in the production of energy would be accounted for.

Scenario 2 started out from the observation, that old cars produce considerably more CO_2 and other emissions than newer ones (Pötscher, 2016). This incited the idea to restrict their usage at least in certain areas, like in urban environments, where population density is very high and air quality is a more pressing issue (Fenger, 1999; Portney and Mullahy, 1986). Finding a specific year for a date at which a car should not be used anymore is delicate, because it influences not only the effect of the policy but also the difficulty of implementing it. For this reason, a large range of years is considered and the effects of these hypothetical policies were estimated. This scenario was implemented by removing all cars that should not be used any longer and replacing each by a random other car that would still be allowed within the city limits. This leaves the distribution of allowed cars constant and does not simply speculate that each old car will be replaced by a newly built one, which would be an unrealistic assumption. Using this modified set of cars, the simulation was performed and the impact of this policy on CO_2 emissions was evaluated.

Scenario 3 had its focus not on a different set of cars in use, but on a different driving behavior of the urban population. Digitalization and automation are changing the job market rapidly (Brynjolfsson and McAfee, 2014; Ford, 2015; Frey and Osborne, 2017), giving more people the possibility to work from home, maybe in the form of a home office or working self-employed as a freelancer (Lindsay and Macaulay, 2004). This transition is especially relevant for urban areas. It gains even more importance, since commuting to work is responsible for a significant fraction of overall traffic. For these reasons the effects that the possibility to work from home has on commute-related CO_2 emissions were evaluated. In order to simulate this change in driving behavior, it is necessary to understand why people use their car, especially whether it is related to work, shopping, leisure or other activities. The presented model has access to these reasons, modeled after statistical data obtained from (Tomschy et al., 2016). That way one can identify all trips that are related to work and remove a certain percentage of them, expressing that such trips may become obsolete due to changes in working behavior.

Scenario 4 envisioned an increased focus on public transport and incentives to use bicycles in an urban environment to reduce private motorized transport (PMT). Public transport has great potential to decrease CO_2 emissions (Rojas-Rueda et al., 2012), but is burdened with large investments. Although it is currently unclear which is the most viable way to make public transport and bicycle use more attractive, the impact of a hypothetical, successful policy can still be evaluated. For this scenario, it was assumed that all routes that are shorter than a specific distance can be completed without the use of a car, either by bicycle or by some form of public transportation and therefore not releasing CO_2 emissions while travelling this trip. This specific distance was varied and it was investigated, if there is an optimal distance, which would be of high interest to policymakers.

Scenario 5 investigated a change in the road infrastructure. A significant portion of CO_2 emissions is caused by congestion and it therefore stands to reason that a decrease in traffic congestions should also lead to a decrease in emissions. In this scenario, the simulation was performed with the parameters of the status quo in order to find the sections of roads with the highest congestion. Then a certain percentage of the most congested road sections are expanded to feature an additional lane. Although such a policy is difficult to implement, since not all road sections can simply be upgraded this way, it is nevertheless interesting to investigate the potential benefits.

Each of the investigated policies might result in a reduction of CO_2 emissions on its own, but the most significant impact is expected, when several policies are combined, which is straightforward within the presented model. Scenario 6 investigated a combination of electric car use, telecommuting and alternatives to PMT.

All these scenarios were run several times with different random seeds, which influence each agent's starting point within a district, the assigned mobility behavior, the assigned car, and other random processes, e.g. scenario effects and destination point selection. The results are evaluated and compared in the following section.

4. Results

4.1. Validation

The base line simulation yielded a result of 484 ± 6 t/day of CO_2 emissions caused by the citizens within the city limits, and an additional 703 ± 15 t/day outside the city limits. This simulated total of 1187 t/day can be used to evaluate the model utilizing statistical data. According to this data, the citizens of Graz produce 1167 t/day of CO_2 emissions by car traffic (Umweltbundesamt, 2015). This implies a relative error of less than 2% and hence seems to substantiate the validity of the model.

In order to evaluate the generation of origin-destination data (see section 3.2) and the resulting congestion (see section 3.3), Fig. 4 shows a comparison between simulated and real traffic congestion on each street during morning rush-hour. Panel a reports the results of the base line scenario, while panel b is extracted from Google Traffic data (typical Tuesday 08:00). It is clearly visible that the simulated traffic pattern is very similar to the real one. Almost all main travel routes through the city are correctly depicted. This fact cannot be taken for granted, since all origin-destination data is generated within the model. It is not provided as input data. This further seems to back up the assumption that the presented method of producing origin-destination data and pathfinding is able to produce realistic road usage.

The following presents the CO_2 emission results from the mentioned simulation scenarios. All results are based on emissions generated by citizens within the city limits. Results are averaged over six simulation runs in order to reduce the statistical error and even out random fluctuations. This number was found in a detailed analysis showing that the relative error, i.e. the standard deviation of CO_2 emissions divided by the square root of number of runs, of the presented model falls below 1% after 6 repetitions of the same scenario, as can be seen in Fig. 5. Therefore, all parameter sets of all scenarios are simulated 6 times, leading to errors of roughly 1% for most of the parameter sets.

Results for scenario 1, simulating an increase in electric cars, are reported in Fig. 6. The results of these simulations are exactly as expected. Since the change from a diesel or petrol car to an electric car has no effect on congestion or other notable secondary effects,

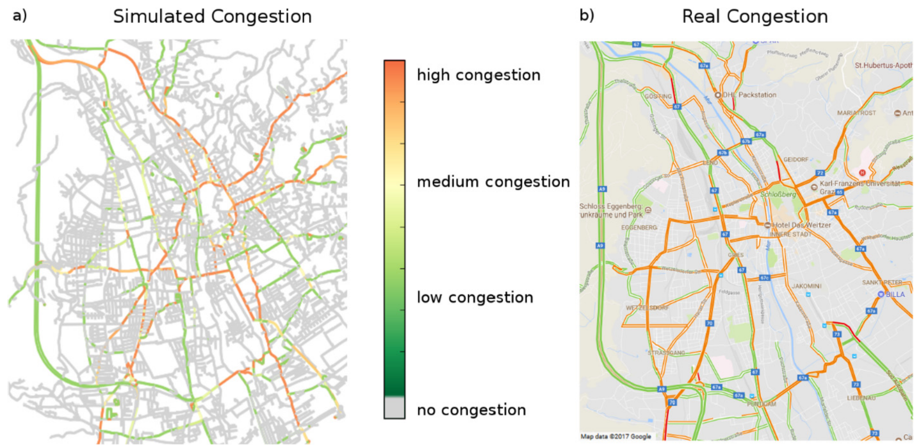

Fig. 4. Simulated congestion (panel a) and real congestion (panel b).

an electric car rate of x% should reduce primary CO_2 emissions by roughly x%. Fig. 6 shows that the results perfectly match the expected behavior and serves as a further evaluation of the validity of the used model. Note, that this figure only shows primary CO_2 emissions. However, depending on how the electricity is produced, electric cars can have significant CO_2 emissions during their lifecycle, possibly resulting in an increase in overall CO_2 emissions (Nicolay et al., 2000).

Scenario 2 investigated the effect of a ban of old cars. Results are shown in Fig. 7. Here an interesting fact about this policy is revealed: This policy is only effective, if relatively new cars would be removed. Replacing only the oldest cars (built before 1995) has only a very minor effect on overall emissions. The main reason for this is that there are only very few cars of that age in the investigated city, so even though they contribute more to CO_2 emissions per car, their aggregated influence is small. Significant improvement could only be achieved by replacing all cars built before 2000, which would be a drastic policy, making it difficult to be implemented by policy makers. However, successfully removing all cars built before 2000 would yield a big reduction of CO_2 emissions of nearly 15%. Note, that this study is only concerned with CO_2 emissions and that for other emissions the effect of banning very old cars may nevertheless be beneficial in terms of air quality in urban areas.

The possible effects of increased telecommuting, the focus point of scenario 3, can be seen in Fig. 8. It is clear that commuting is

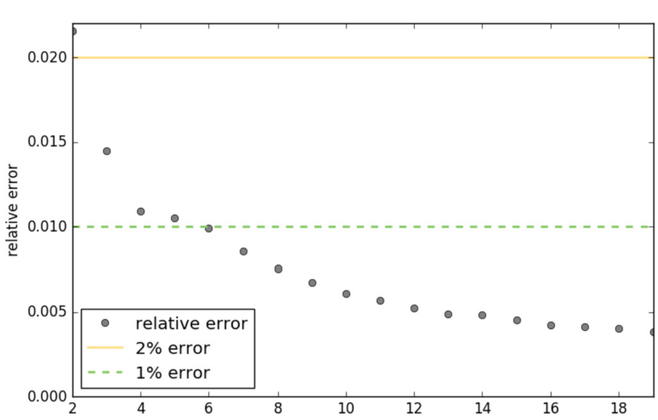

Fig. 5. Development of the relative error with the number of performed simulation runs.

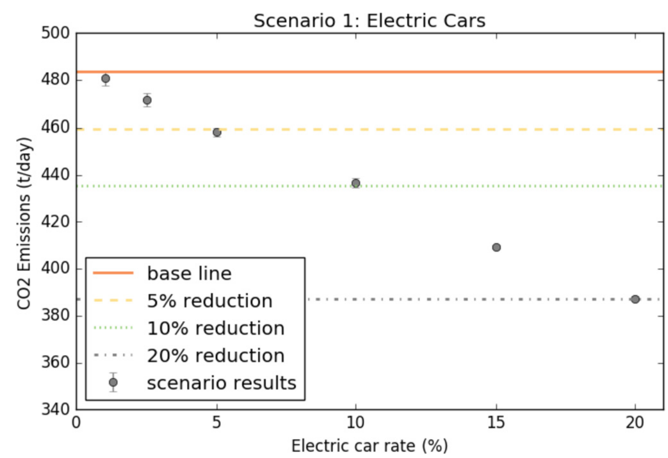

Fig. 6. Results of scenario 1: The CO_2 emission impact of electric car use.

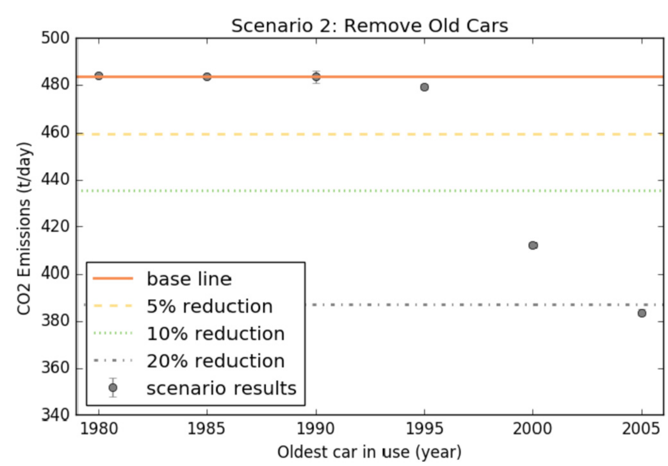

Fig. 7. Results of scenario 2: The CO_2 emissions impact of removing old cars.

responsible for a huge fraction of CO_2 emissions in an urban area, but there are also secondary effects that make a reduction of commuting a promising policy. With fewer commuters there is also less traffic during peak hours and the increased emissions due to congestion and stop-and-go traffic are reduced. In the base line scenario 16.4% of emissions are caused by congestion effects, while

here the share of congestion caused emissions is between 15.2% and 9.6%, nonlinearly depending on policy intensity.

Fig. 9 illustrates the effects of increased public transport and bicycle use, investigated in scenario 4. The effect is mainly caused by the reduction of trips as the share of congestion related emissions (between 16.3% and 15.3%) is close to the one in the base line scenario (16.4%). This scenario reveals an interesting feature: While stopping to use cars for distances smaller than 2000 m has only a small effect on overall CO_2 emissions, an increased minimal car travel distance can lead to significant improvements. This has to do with the fact, that many of the routes smaller than 3 km are completed without cars, even in the base line scenario of the investigated city. This fact may be of great relevance for policy makers, since it suggests that in order to decrease CO_2 emissions from PMT it is necessary to provide more alternatives that are attractive for distances of 3 km and above.

Fig. 10 presents the results of an expansion of the road network to increase its capacity, investigated in scenario 5. The findings of this scenario are intriguing. Adding an additional lane to the most frequented road sections has no significant effect on emissions, even when one tenth of all road sections are expanded that way. Only for higher values, like upgrading the top 12.5% of road sections, the effect of such a policy is measurable. The main reason for this is that most roads are congested only during peak hours, and one additional lane does little to solve this problem. Combined with the immense cost, the problematic feasibility and the fact, that broader roads might encourage PMT and could have a negative effect on emissions, this scenario reveals that it is not viable to reduce urban CO_2 emissions by increasing the capacity of an urban road network.

Fig. 11 shows the results from the combination of three policies: electric car use, telecommuting and alternatives to PMT. The x-axis shows electric car rate in percent, telecommuting in percent and the smallest distance for car use, measured in units of 10^4 m, for simplified comparability. As expected, combining different policies yields the biggest result in emission reduction, yet the overall effect is slightly smaller than the sum of the individual effects of each policy (<3%), since one trip could be affected by multiple policies leading to a reduced overall effect. Table 5 sums up the results of all considered scenarios.

5. Discussion

This study finds that all investigated scenarios have the potential to decrease urban CO_2 emissions. However, the possible effect that can be achieved with each scenario varies. In addition, the actual implementation of policies leading to some of these scenarios represents a challenge, so that some scenarios are more viable than others.

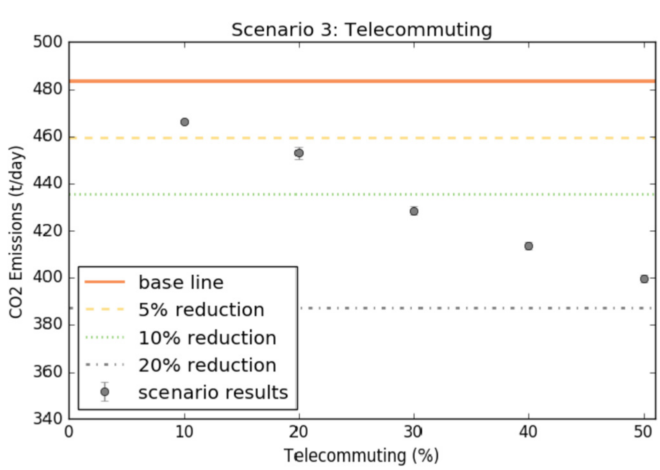

Fig. 8. Results of scenario 3: The CO_2 emission impact of telecommuting.

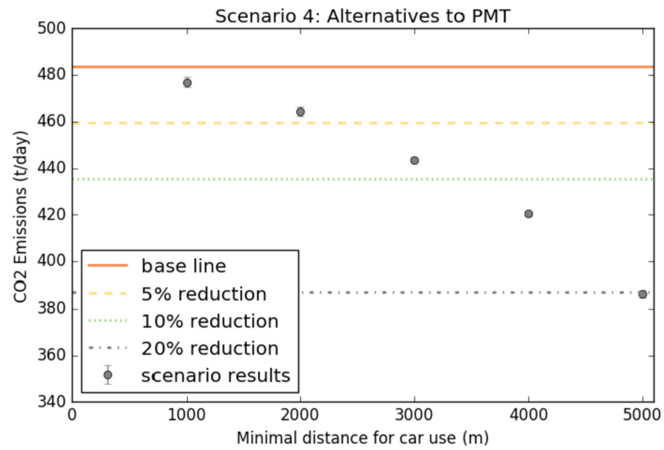

Fig. 9. Results of scenario 4: The CO_2 emission impact of alternatives to PMT.

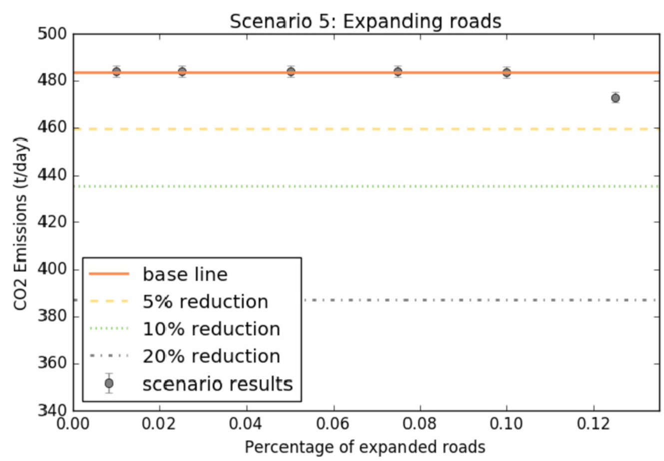

Fig. 10. Results of scenario 5: The CO_2 emission impact of expanding the road network.

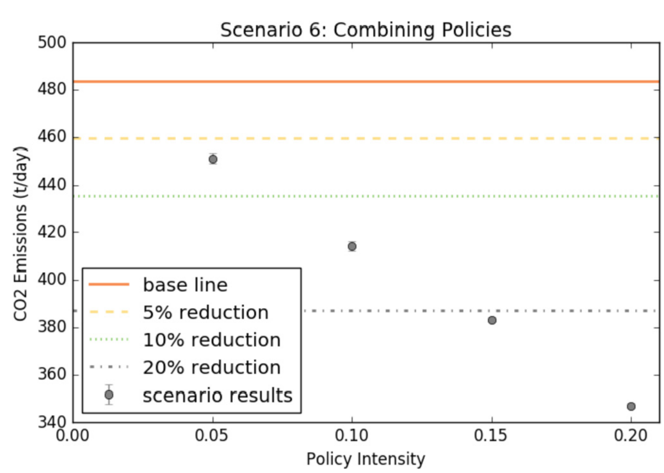

Fig. 11. Results of scenario 6: The CO_2 emission impact of a combination of electric cars, telecommuting and alternatives to PMT. "Policy Intensity" refers to the electric car rate in percent, the telecommuting factor in percent, and the minimal car use distance in units of 10^4 m.

Table 5
Overview over scenario results.

Scenario	Max effect in considered range	Dependency on policy intensity	Feasibility
Electric cars	≈20%	Linear	High for low intensity
Remove old cars	≈21%	Minimal effect for removing only cars from 1995 or older	Difficult for the effective intensity
Telecommuting	≈17%	Nearly linear	Very dependent on profession
Alternatives to cars	≈20%	Very steep for distances over 3 km	High for low intensity (bus, bikes), but higher intensity (≥3 km) need new ideas
Expanding roads	≈2%	No effect for expanding 10% of roads or less	Very difficult for most cities
Combination	≈28%	Nearly linear	High for low intensity

Investing in a better road infrastructure showed the smallest effect of all investigated policies, while being one of the most expensive and most difficult policies to implement. Combined with the negative repercussions of encouraging PMT, this policy seems unfit to effectively reduce CO_2 emissions.

The impact of replacing old cars by newer cars is sensitive to the number of cars replaced. Replacing only very old cars might be easier to implement for policy makers, but the effects of such a policy on CO_2 emissions are minor, especially if the total number of old cars is small, which is true for the investigated city. The more cars are replaced, the more CO_2 can be reduced, but also the implementation of such a policy would be more challenging. Here it is important to mention, that only CO_2 emissions are investigated. The presented investigation was not concerned with the effects on other types of emissions. Especially in order to deal with the problem of fine dust it is often discussed to outlaw old diesel engines, which may very well have a significant effect on air quality.

An increase in telecommuting is a very promising way to reduce CO_2 emissions, especially in an urban environment, where traffic caused by commuters has many other negative effects on a densely populated area. Telecommuting offers a primary reduction of CO_2 emission, simply because less people have to use their cars, but also secondary effects, because congestion during peak hours is significantly reduced.

Electric car use can have a huge impact on traffic related emissions, especially in cities, where the public sector has many opportunities to offer incentives for electric car use (better charging infrastructure, free parking or the use of bus lanes, etc.). In addition, one of the barriers for the diffusion of electric cars that is most difficult to overcome is the limited range of electric vehicles. In an urban environment however, this disadvantage is less relevant, at least for traffic within the city. An additional benefit of an increased use of electric cars, beyond climate change mitigation through lower CO_2 emissions, is a positive effect on urban air quality, caused by the negligible emissions of electric engines.

An interesting result was obtained in the scenario that dealt with offering alternatives to PMT. One of the main alternatives to motorized transport is the use of a bicycle and it is often assumed that cities should focus on providing incentives for bicycle use in order to combat emissions. While this is still true, the model shows that there is even higher CO_2 reduction potential for distances above 3 km. It is therefore of high relevance to address this problem and offer other alternatives to PMT that are viable for distances above 3 km, like for example e-bikes.

The scenario of combined policies yielded promising results, as the sum of the effects is only slightly smaller than the individual effects. Thus, combining policies is a reasonable approach, since it can be less difficult to implement several policies with low intensity than a drastic, but effective one.

Based on these results possible policy recommendations are that an investment in additional road infrastructure offers no significant benefit, while the replacement of old cars is viable, as long as enough cars are replaced (here: all cars built before the year 2000). This could possibly be achieved by convincing users of old cars to switch to new, eco-friendly models by offering monetary incentives directly linked to the age of the replaced car.

Some limitations concerning the presented model need to be addressed. First of all, only primary traffic emission is considered, so the emissions caused by providing the electricity for electric cars, but also the emission caused by the production process of diesel and petrol are out of scope of this model. For a detailed analysis of these effects, see for example (Nicolay et al., 2000). Therefore, if the electricity for the electric cars does not come from emission-free sources, the model overrates the global impact of electric cars. However, in this case the effect is diminished by the fact that Austria produces most of its energy from hydroelectric power plants (Eigenbauer and Urbantschitsch, 2016), which have a low emission of GHG (Turconi et al., 2013). Also other secondary effects are not included in the model. E.g. telecommuting would lead to an increased need for heating homes, yet this effect would probably be compensated by the decreased number of offices. However, the presented model is capable of evaluating the primary effects on urban traffic emission and can point out possible policies, which can then be scanned for secondary effects with more appropriate methods, like life-cycle assessment.

There are several possible expansions conceivable which would increase the scope and the predictive power of the model. First of all, it might be beneficial to increase the investigated region and population in order to depict more causes for CO_2 emissions. In addition to that, it would be interesting to include public transport in greater detail in order to experiment with the placement, positioning and frequency of stops. A detailed description of bicycle lanes could bring more insight into why alternatives to PMT are used for some routes and not for others. Another expansion could deal with other emissions than CO_2, for example fine dust, which has a completely different behavior from CO_2 regarding local and global effects and regarding emission rates for different car types and car ages. This approach would have the additional effect of not only addressing CO_2 emissions with their global effect, but also other emissions with rather localized effects. These could be of more interest to regional policy makers.

In conclusion, this study was able to provide quantitative results to specific scenarios and can be adapted to be used for other cities as well. Even though detailed mobility data may not be available for every city, using aggregated data of cities of similar size can also produce meaningful results. In addition to evaluating the different scenarios shown in this study, the presented approach offers a possibility to evaluate various scenarios, like technological changes (e.g. eco-friendlier engines), societal changes (e.g. less shopping trips due to increased online shopping), juridical changes (e.g. no PMT within the inner city) or changes in infrastructure (e.g. more e-mobility hotspots), all within the same framework. Most other approaches to calculating urban traffic emissions are very detailed and specialized on car trajectories, and therefore lack the flexibility to evaluate scenarios that are highly diverse. Offering a framework for such investigations is an important purpose of the presented

model, since this contributes to the progress of the state-of-the-art of urban emission modeling. Furthermore, it serves as a starting point with the final goal of obtaining a more complete picture of urban mobility and emissions within an agent-based network framework.

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